3D REGION GROWING INTEGRATING ADAPTIVE SHAPE PRIOR

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ABSTRACT

We propose an automated region growing integrating adaptive shape prior in order to segment biomedical images. In our work, the segmentation method is improved by taking into account a shape reference model by non-linear way. Thus, the proposed method is driven by statistical data computed from the evolving region and by a priori shape information given by the model. An improvement of the method is proposed by adapting automatically the degree of integration of shape prior for each pixel of the image. The proposed method was applied for segmenting 3D micro-CT image of mouse skull in the framework of small animal imaging. The method gives promising results and appears to be well adapted to the context.

Index Terms— Shape, image segmentation, region growing, biomedical imaging

1. INTRODUCTION

Advanced radiological imaging techniques have been largely employed to detect and quantify anatomical structures. The wide variety of organs, noise and low contrast increase the complexity for feature extraction and quantitative analysis. So, the segmentation becomes an important step in medical image processing. Classical segmentation algorithms are generally guided by forces resulting from image information and a regularizing term [1]. The first force is computed from image data whereas the second expresses some properties of the region contour. Nonetheless, this information is not sufficient to segment accurately occluded objects or objects with a partially badly defined boundary. To face this problem, additional information like prior knowledge can be used to improve the result of segmentation.

The integration of shape information in segmentation induces the choice of a shape representation as a reference surface or volume. In the current shape prior framework, the main objective is to tolerate a possible variation between the target object and the model. The quantification of this variation implies the definition of a distance between the evolving region and the reference model. Cootes et al. [2] proposed the Active Shape Model (ASM) where the shape model is represented by a distribution of points around the reference contour. Gastaud et al. [3] introduced a shape prior term as the Euclidean distance between the evolving contour and a reference model. In [4], Cremers et al. presented a variational approach incorporating shape dissimilarity term into level set method. They were integrating a symmetric pseudo-distance by using the signed distance function characteristic used in level-set methods.

In this work, we propose to improve the performance of region growing approaches by taking into account shape information. In this method, the target object is modeled by a reference volume. An optimization step is applied to automatically and locally balance the degree of shape prior and image data information. The tests on 3D experimental data will demonstrate that prior information enables achieving a correct segmentation despite high noise or corruption.

2. METHOD

The main objective of this work is to integrate global shape prior in the process of region growing. The reference model, allows assessing a distance between the boundaries of the evolving region and the reference model. This term will be integrated in region growing as a shape prior.

2.1. Principle of region growing

In region growing approaches [5], the merge of a pixel to the evolving region is governed by an aggregation criterion which must be satisfied. At each step, a set of candidate pixels not belonging but neighboring to the evolving region are tested. Candidate pixels which satisfy the aggregation criterion are added to the evolving region, which results in a new region. We define a studied pixel as a pixel belonging to the evolving region and located on its contour. Let us note $\varphi(x) \in [0, 1]$ the function used for assessing the aggregation criterion for a pixel x. The aggregation criterion is true when:

$$\varphi(x) \geq \delta \qquad (1)$$

where $\delta \in [0, 1]$ is a given threshold. So, aggregation criterion is a Boolean term based on a functional computed from

region's features. Initially, these features are estimated from seeds and their neighbors and then, measured from the evolving region at each step.

2.2. Region growing integrating shape prior

Three dimensional region growing based on grey level intensity has many advantages (free spreading of the segmentation) but is sensitive to leaks. Our method [6] aims to improve this technique by constraining the spread with shape prior. In this work, the criterion is computed from two functions $\varphi_{region}(x)$ and $\varphi_{shape}(d(x, \Gamma^{ref}))$ as expressed in the following equation:

$$\varphi(x) = \varphi_{region}(x) \times \varphi_{shape}(d(x, \Gamma^{ref})) \qquad (2)$$

Where x is a pixel of image and $d(x, \Gamma^{ref})$ is the normalized signed Euclidean distance between a pixel x and the reference contour Γ^{ref}.

2.2.1. Statistic assessment

$\varphi_{region}(x) \in [0, 1]$ is the term related to image data. It measures the similarity between $I(x)$ the grey level of a candidate pixel x and the distribution of grey levels in the evolving region R^{in}. In this work, we assume that the underlying distribution of grey levels in R^{in} is approximated by a gaussian distribution with mean $\mu_{R^{in}}$ and standard deviation $\sigma_{R^{in}}$. $\varphi_{region}(x)$ represents the similarity between a candidate pixel and the gaussian distribution of the region. In the iterative region growing process, $\mu_{R^{in}}$ and $\sigma_{R^{in}}$ are estimated at each step.

2.2.2. Shape prior assessment

$\varphi_{shape}(d(x, \Gamma^{ref})) \in [0, 1]$ expressed in equation 3 is related to geometrical features of the evolving region. The signed Euclidean distance function was introduced by Danielson et al. [7]. By definition, $d(x, \Gamma^{ref})$ is equal to the signed distance from x to the nearest pixel belonging to the reference contour normalized by the absolute value of the minimum signed distance. Once and for all, $d(x, \Gamma^{ref})$ is computed for each pixel of the image and stored in a distance map. A negative (resp. positive) value indicates that the pixel is inside (resp. outside) the reference region. Instead of directly using the normalized signed distance $d(x, \Gamma^{ref})$, we propose to define $\varphi_{shape}(d(x, \Gamma^{ref}))$ as a non linear function of this distance.

$$\varphi_{shape}(d(x, \Gamma^{ref})) = \frac{\frac{\pi}{2} - \tan^{-1}\left(\left(\lambda \times d(x, \Gamma^{ref})\right)^3\right)}{\pi} \qquad (3)$$

where λ is a tuning parameter. It can be noticed that $\varphi_{shape}(d(x, \Gamma^{ref}))$ depends on the affine position of the reference object. Therefore, a previous affine registration is
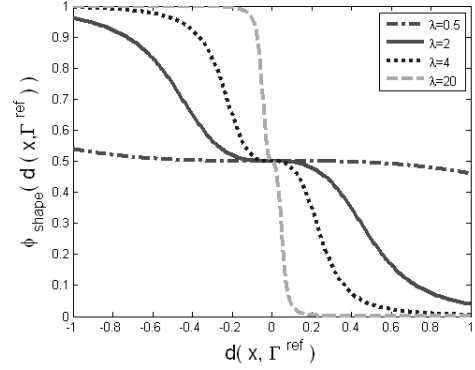
Fig. 1: $\varphi_{shape}(d(x, \Gamma^{ref}))$ for different λ values.

required between the reference model and the original image. As we can see on figure 1, when $d(x, \Gamma^{ref})$ is negative i.e. x is inside the reference object, $\varphi_{shape}(d(x, \Gamma^{ref}))$ takes a value close to 1, thus helping the aggregation of x. When $d(x, \Gamma^{ref})$ is positive i.e. x is outside the reference object, $\varphi_{shape}(d(x, \Gamma^{ref}))$ takes a value close to 0, thus acting against the aggregation of x. Thus, parameter λ is related to the magnitude of integrating shape prior in the segmentation.

3. ADAPTIVE SHAPE PRIOR

A major drawback of the previous criterion is the setting of the global λ hyper-parameter. Thus, λ value must be experimentally adjusted by trial and error. In order to overcome the problem, λ value will be adjusted automatically for each pixel of the image. We propose to use the Gradient Vector Flow (GVF) and the growing direction $\overrightarrow{D}(x)$ of the region growing for adapting shape prior in the segmentation.

3.1. Basic background

The GVF term provides two kinds of information: the proximity of the nearest boundaries and the direction toward the boundaries.
GVF $\overrightarrow{v}(x, y, z) = [u(x, y, z), v(x, y, z), k(x, y, z)]$ is defined as the vector field that minimizes the following function:

$$\varphi_{GVF} = \int\int\int \mu (\eta_u + \eta_v + \eta_k) |\nabla f|^2 |\overrightarrow{v} - \nabla f|^2 dxdydz \qquad (4)$$

where $\eta_u = u_x^2 + u_y^2 + u_z^2$, $\eta_v = v_x^2 + v_y^2 + v_z^2$, $\eta_k = k_x^2 + k_y^2 + k_z^2$ and f an edge map derived from the image. μ is a noise control parameter. The main interests of the GVF are its large capture field and its oriented field. These kinds of information will be useful to compute the local λ value. The growing direction $\overrightarrow{D}(x)$ is defined by the vector between a studied pixel x and one of its candidate pixels $x_c \in \Omega$.

3.2. Adaptive λ parameter

A link between λ value, GVF and $\overrightarrow{D}(x)$ is established from the following observations shown in figure 2.

Firstly, if the GVF vector defined at one pixel and the growing direction at the studied pixel have the same direction, image data will be sufficient to drive the region growing, so λ can be relaxed to limit the influence of the shape prior.

Secondly, with a low GVF vector or if the GVF direction has an opposite direction to the growing direction, a high λ value is necessary, because there is a lack of gradient information which must be compensated by shape prior.
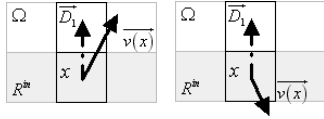
Fig. 2: Link between GVF field and Growing Direction.

In equation 5, we define $P_{GVF}(x)$ as the scalar product between the GVF vector and the growing direction.

$$P_{GVF} = \overrightarrow{v}(x) . \overrightarrow{D}(x) \qquad (5)$$

Growing direction vector and GVF vector are previously normalized to limit $P_{GVF}(x)$, so that $P_{GVF}(x) \in [-1, 1]$. We propose to determine automatically λ value by taking into account the information given by $P_{GVF}(x)$. If a high GVF vector is defined at one pixel and the growing direction is similar, $P_{GVF}(x)$ is close to 1 so λ_x value can be relaxed to limit the shape prior.

The λ_x parameterization is obtained by equation 6.

$$\lambda_x = \left(\frac{\lambda_{\min} - \lambda_{\max}}{2} \right) \times P_{GVF}(x) + \frac{\lambda_{\max} + \lambda_{\min}}{2} \quad (6)$$

where $\lambda_{\min}$ and $\lambda_{\max}$ are the bounds of λ_x value. For a high $P_{GVF}(x)$, λ_x value is close to $\lambda_{\min}$ i.e. integration of low shape prior. For a low $P_{GVF}(x)$, λ_x value is close to $\lambda_{\max}$ i.e. integration of high shape prior. Thus, equation 6 allows to adapt automatically the λ_x value according to image data.

4. EVALUATION AND APPLICATION

4.1. Evaluation on 2D synthetic image

We experiment the method on 2D noisy synthetic image in order to assess the performance of our method. Figure 3(a) represents the object of interest i.e. the targeted object.

Figure 3(c) represents the image to segment where Gaussian noise with a standard deviation equal to 20 and corruption were added. A leaking point appears at the bottom left of the image and a second handle is added. Figure 3(b) displays the reference model used as shape prior. We can notice that the
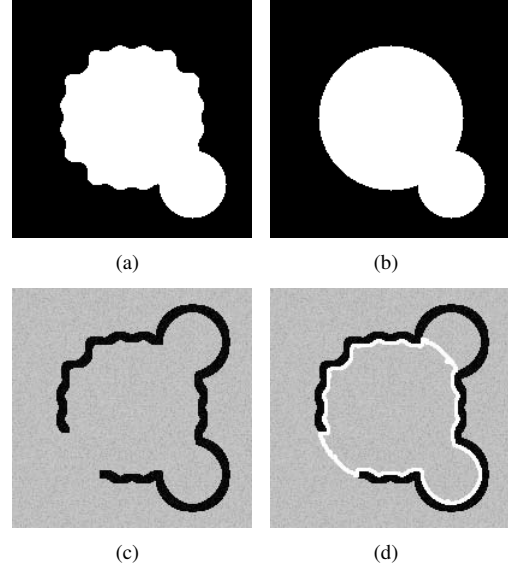
Fig. 3: Synthetic image: a) theoretical object, b) reference model, c) image to segment, d) result image.

shape model differs slightly from the theoretical object.

Figure 3(d) shows the result of the method with adaptive shape prior. The white contour delineates the segmented region. Without shape prior, the method fails to segment the object by aggregating pixel in the wrong handle and spread by the point leak.

4.2. Experimental 3D image presentation

The method was applied in the framework of small animal imaging, provided by the small animal imaging facility Animage. The aim of this application is the mouse phenotyping by intracranial cavity volume analysis (Figure 4(a)). We tested the method on micro-CT 3D images of mouse skull acquired with 35μm isotropic resolution.

The 3D reference model shown in figure 4(b) is manually delineated by a medical expert from one volume defined as the reference volume. The same reference model is used for all segmentations. Before each segmentation, this reference model is affinely registered using ITK, an open-source library (http://www.itk.org/). The registration is computed from the mean squared pixel-wise difference in intensity between two images over a defined region. Poor matches between two images result in a large value of the metric. Then a seed is set with a random position inside the studied skull to initialize the process.

4.3. Results of adaptive λ parameter

We have tested our algorithm on four micro-CT images. In figure 5, the white contours delineate the segmented regions. From these examples, it appears that our method successfully
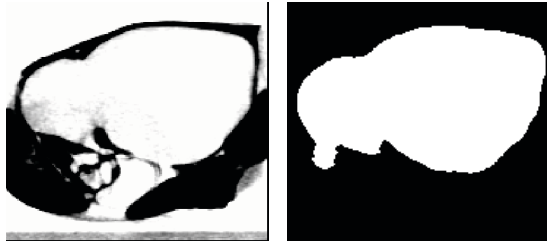
Fig. 4: a) Initial 3D image of mouse skull, b) Reference image.

extracts the region of interest from the images. In figure 5(c) and figure 5(d), region growing has not spread toward the leaking points located at the bottom of the skull. Our segmentation achieves a good segmentation of objects: their resulting shape is similar to the shape model even though the image is occluded or has a highly variable contrast.

Adaptive λ value allows adapting automatically the shape prior in the segmentation, by relying on image data. Figure 5(a) shows that our adaptive method takes mainly into account image information when image data are enough relevant to drive the segmentation.

On the contrary, a high shape prior is used when image data are not significant or missing, thus avoiding leaking points (see figure 5(c) and 5(d)).
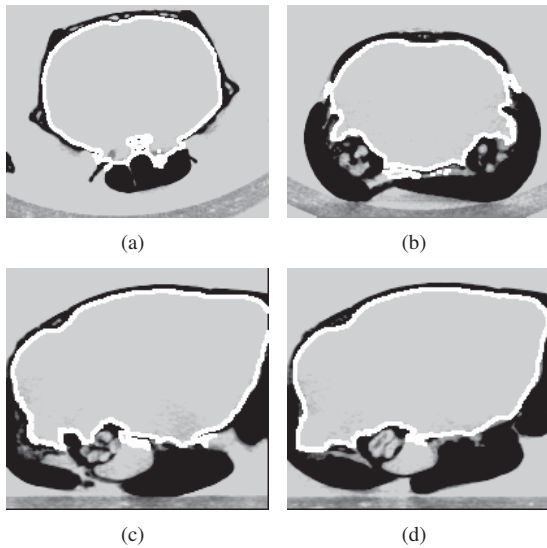
Fig. 5: Segmentation results with adaptive λ value.

5. CONCLUSION

In this paper, we have proposed a new automated region growing integrating adaptive shape prior. This geometric prior is based on a reference model which can more or less constrain

the process of region growing. The adaptability of the process is computed from the Gradient Vector Flow and the growing direction. This improvement increases the robustness of the method and the quality of the segmentation results.

Our method has been tested and applied on micro-CT scans of mice's skulls in order to confirm the performance of shape prior influence. Our experimental results are coherent with the sought object, thus demonstrating the efficiency of our method for automated segmentation.

7. REFERENCES

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